**A PROJECT REPORT ON**

**Real Time Object Detection Using YOLO**

Submitted in fulfillment of the requirements for the award of the Degree of

**BACHELOR OF COMPUTER APPLICATIONS**

In

**INFORMATION TECHNOLOGY & COMPUER APPLICATIONS**

By

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**CERTIFICATE**

This is to certify that the project entitled “E-Commerce Application” being submitted by *P. Sai Abhinay (211FJ01048)* in partial fulfillment of Bachelor of Computer Applications in the Department of Information Technology, Vignan’s Foundation for Science Technology and Research, Vadlamudi, Guntur District, Andhra Pradesh, India, is a bonafide work carried out by him under our guidance and supervision.

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**DECLARATION**

I hereby declare that my project work described in this project titled “Real Time Object Detection Using YOLO” which is being submitted by me for the partial fulfillment of Bachelor of Computer Applications in the Department of Information Technology, Vignan’s Foundation For Science Technology and Research, Deemed to be university Vadlamudi, Guntur District, Andhra Pradesh, and the result of investigations are carried out by me under the guidance of Mr. Sk. Nyamathulla*.*

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**ABSTRACT**

Real-time object detection is a crucial component in various applications such as autonomous vehicles, surveillance systems, and human-computer interaction. In recent years, deep learning-based approaches have demonstrated remarkable performance in this domain. Among them, You Only Look Once (YOLO) stands out for its ability to achieve high accuracy while maintaining real-time processing speeds. This project focuses on implementing real-time object detection using YOLO, a state-of-the-art convolutional neural network (CNN) architecture. Through this work, we aim to explore the capabilities of YOLO in detecting objects accurately and efficiently in live video streams. The project involves understanding the underlying architecture of YOLO, training the model on a suitable dataset, optimizing it for real-time performance, and integrating it into a practical application. Key components of the project include dataset preparation, model training, evaluation, and deployment. We leverage popular deep learning frameworks such as TensorFlow or vscode for implementation, taking advantage of their robust tools for model training and deployment. Additionally, we explore techniques for optimizing inference speed without compromising accuracy, crucial for achieving real-time performance in resource-constrained environments. The project's outcomes will include a comprehensive analysis of YOLO's performance in real-time object detection tasks, along with insights into optimizing deep learning models for efficiency. Furthermore, we will present a practical application showcasing the real-world utility of our implementation, demonstrating its potential in various domains where real-time object detection is essential. Overall, this project contributes to advancing the field of computer vision by harnessing the power of deep learning for real-time object detection, with YOLO serving as a prominent example of cutting-edge technology in this domain.

**CHAPTER-1**

**INTRODUCTION**

In an era dominated by smart devices and automation, real-time object detection serves as the backbone for numerous applications, spanning from security surveillance to augmented reality experiences. The ability to accurately and efficiently identify objects in live video streams is not only a technical challenge but also a critical requirement for enabling advanced functionalities in various domains.

This project delves into the realm of real-time object detection using YOLOv3, with a particular focus on optimizing its deployment for low-end devices. While YOLOv3 excels in performance, its resource-intensive nature poses challenges for deployment on devices with limited computational capabilities, such as embedded systems, smartphones, and IoT devices. The primary objective of this project is to bridge this gap by tailoring YOLOv3 to operate efficiently on low-end hardware, without compromising its real-time processing capabilities.

The project unfolds through several interconnected stages. Initially, a comprehensive understanding of YOLOv3's architecture and functionality is established. This is followed by the selection and preparation of a suitable dataset for model training, a crucial step in ensuring robust detection performance across various object classes and scenarios. Subsequently, the YOLOv3 model undergoes rigorous training and optimization processes, aimed at reducing its computational complexity and memory footprint while preserving its high detection accuracy.

The outcomes of this project are twofold. Firstly, a comprehensive analysis of YOLOv3's performance on low-end devices is presented, encompassing metrics such as accuracy, inference speed, and resource utilization. Secondly, a practical application demonstrating the real-world deployment of optimized YOLOv3 models on low-end hardware is showcased, illustrating the feasibility and efficacy of the proposed approach in real-time object detection scenarios.

**CHAPTER-2**

**PROBLEM STATEMENT**

**OBJECTIVES**

2.1 PROBLEM

Object detection on low-end devices presents a significant challenge due to their constrained computational resources. These devices, including embedded systems, smartphones, and IoT devices, often struggle to handle the computational demands of deep learning models like YOLOv3 while maintaining real-time performance. This dilemma highlights the inherent trade-off between accuracy and efficiency in object detection tasks, exacerbated by the limitations of low-end hardware. Achieving high accuracy in real-time object detection without sacrificing efficiency is crucial for the effective deployment of intelligent applications in resource-constrained environments. Inadequate computational power often leads to slower inference speeds and reduced detection performance, hindering the practicality and efficacy of these systems. Existing solutions tend to prioritize either accuracy or efficiency, failing to strike an optimal balance that meets the requirements of low-end devices. The disparity in model performance between high-end and low-end devices underscores the pressing need for tailored solutions that address the unique challenges posed by resource-constrained environments. Overcoming this challenge necessitates innovative approaches that optimize model performance specifically for low-end devices, ensuring equitable access to real-time object detection capabilities across diverse hardware platforms.

2.2 PURPOSE

The primary purpose of this project is to empower low-end devices to perform real-time object detection tasks effectively, thereby democratizing access to advanced computer vision functionalities. By enhancing the capabilities of low-end hardware, this initiative aims to bridge the gap between high-end and low-end devices in terms of object detection performance. Enabling real-time object detection on low-end devices holds immense potential for deploying intelligent applications in diverse settings, including IoT, surveillance, and healthcare. This endeavor extends beyond technical innovation to drive societal impact, fostering inclusivity and accessibility in technology adoption. Realizing real-time object detection on low-end devices can revolutionize industries and improve quality of life by making intelligent systems more accessible and pervasive. By ensuring that advanced technologies are available to all, regardless of hardware constraints, this project seeks to bridge the digital divide and promote equitable access to AI-driven solutions.

2.3 SOLUTION

The solution to the challenges posed by real-time object detection on low-end devices involves optimizing the YOLOv3 architecture and deployment process specifically for these platforms. This optimization effort encompasses various techniques aimed at reducing the computational and memory requirements of YOLOv3 while preserving its high detection accuracy. Techniques such as model quantization, layer pruning, and network architecture modifications are explored to streamline the model and ensure compatibility with the computational constraints of low-end hardware. Additionally, lightweight deep learning frameworks and hardware acceleration mechanisms are leveraged to facilitate efficient execution of YOLOv3 models on low-end devices. By prioritizing energy efficiency and streamlining the inference process, the solution aims to achieve real-time object detection speeds while prolonging device battery life. This holistic approach addresses both computational and energy constraints inherent in low-end devices, paving the way for ubiquitous deployment of real-time object detection systems across diverse hardware platforms.

**CHAPTER-3**

**LITERATURE SURVEY**

* 1. **You Only Look Once: Unified, Real-Time Object Detection (YOLO) by Joseph Redmon et al. (2016):**
  + Methodology: YOLO introduced a one-stage object detection framework that divides the input image into a grid and predicts bounding boxes and class probabilities for each grid cell.
  + Accuracy: YOLO achieved impressive mean Average Precision (mAP) scores of around 63.4% on the VOC 2012 dataset and processed images at over 45 frames per second (FPS) on a GPU.

**3.2 Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks by Shaoqing Ren et al. (2015):**

* + Methodology: Faster R-CNN introduced a two-stage object detection framework comprising a region proposal network (RPN) and a region-based CNN for object detection.
  + Accuracy: Faster R-CNN achieved state-of-the-art mean Average Precision (mAP) scores of around 73.2% on the VOC 2012 dataset and processed images at around 5 frames per second (FPS) on a GPU.

**3.3 Single Shot Multibox Detector (SSD) by Wei Liu et al. (2016):**

* + Methodology: SSD introduced a one-stage object detection framework that directly predicts bounding boxes and class probabilities from feature maps at multiple scales.
  + Accuracy: SSD achieved competitive mean Average Precision (mAP) scores of around 74.3% on the VOC 2007 dataset and processed images at over 20 frames per second (FPS) on a GPU.
  1. **MobileNetV2: Inverted Residuals and Linear Bottlenecks by Mark Sandler et al. (2018):**
  + Methodology: MobileNetV2 presented a lightweight neural network architecture optimized for mobile and embedded devices, leveraging inverted residuals and linear bottlenecks.
  + Accuracy: MobileNetV2 achieved state-of-the-art performance on ImageNet classification with an accuracy of over 71%, demonstrating its efficiency and effectiveness for real-time applications.

**3.5 EfficientDet: Scalable and Efficient Object Detection by Mingxing Tan et al. (2020):**

* + Methodology: EfficientDet proposed a scalable object detection framework that achieves state-of-the-art performance across various model sizes through compound scaling and efficient architecture design.
  + Accuracy: EfficientDet achieved top results on the COCO dataset, surpassing previous state-of-the-art methods with higher mean Average Precision (mAP) scores and processing images at real-time speeds.

**CHAPTER-4**

**EXISTING SYSTEM**

The existing system represents a sophisticated approach to real-time object detection, leveraging the capabilities of TensorFlow as the underlying deep learning framework and the Faster R-CNN (Region-based Convolutional Neural Network) model for accurate and efficient detection tasks. TensorFlow's flexibility and extensive ecosystem make it a popular choice for developing deep learning models, while Faster R-CNN's region-based approach enables precise localization of objects within images. These components work synergistically to achieve high detection accuracy across various object classes and scenarios. However, the computational demands of TensorFlow and the complex architecture of Faster R-CNN require substantial processing power, typically available on high-end devices. As a result, the existing system's effectiveness is contingent on the availability of robust computational resources, limiting its deployment to environments where such resources are readily accessible. Moreover, the energy-intensive nature of these models may pose challenges in scenarios where energy efficiency is paramount, such as battery-powered devices or edge computing applications. Despite its effectiveness in achieving accurate object detection, the existing system's reliance on high-end hardware restricts its practical applicability in resource-constrained settings.

**CHAPTER-5**

**PROPOSED SYSTEM**

In contrast, the proposed system introduces a paradigm shift in real-time object detection by leveraging YOLO (You Only Look Once) technology tailored for deployment on low-end devices. YOLO's innovative architecture, characterized by its single pass approach to object detection, offers a compelling solution to the challenges posed by resource-constrained environments. By eliminating the need for complex region proposal networks and leveraging a unified convolutional neural network (CNN) architecture, YOLO achieves impressive detection accuracy while maintaining real-time processing speeds. The proposed system capitalizes on YOLO's efficiency and accuracy, optimizing model architectures and inference processes specifically for low-end hardware platforms such as embedded systems, smartphones, and IoT devices. This optimization enables the proposed system to deliver real-time object detection capabilities without compromising accuracy, thus democratizing access to intelligent applications across diverse hardware ecosystems. Furthermore, YOLO's streamlined architecture and efficient inference process contribute to reduced computational complexity and energy consumption, making it well-suited for deployment in energy-constrained scenarios. By embracing YOLO technology, the proposed system not only addresses the limitations of traditional approaches but also opens up new avenues for innovation and application in resource-constrained environments.

**CHAPTER-6**

**SYSTEM REQUIREMENTS**

**6.1 HARDWARE REQUIREMENTS**

* **Development Workstation:**

A modest workstation with sufficient computational resources for model development and experimentation.

Specifications include a dual-core or quad-core CPU (Intel Core i3 or AMD Ryzen 3), 8GB of RAM, and a basic GPU (integrated or entry-level dedicated GPU).

* **Low-End Devices:**

Target devices with limited computational resources, such as embedded systems (e.g., Raspberry Pi), low-end smartphones, or IoT devices.

Specifications may vary depending on the specific device but typically include a single-core or quad-core CPU, 1GB to 2GB of RAM, and minimal GPU capabilities (if any).

* **Storage:**

Adequate storage space for storing datasets, trained models, and intermediate files.

Affordable storage options such as microSD cards or USB flash drives are sufficient for most low-end devices.

* **Additional Hardware:**

GPU Acceleration (optional): While low-end devices may not have dedicated GPUs, leveraging GPU acceleration during development on the workstation can expedite model training. However, GPU acceleration is not a strict requirement for the deployment of models on low-end devices.

* **Power Supply:**

Ensure access to stable power sources or battery backups to sustain prolonged operation, particularly for embedded systems or IoT devices.

**6.2 SOFTWARE REQUIREMENTS**

* **Visual Studio Code (VSCode):**

A lightweight yet powerful code editor with extensive support for Python development, including syntax highlighting, code completion, and debugging capabilities.

* **Python Extension:**

Install the Python extension for VSCode to enable Python language support, code linting, and virtual environment management directly within the editor.

* **TensorFlow or PyTorch:**

Integrate TensorFlow or PyTorch into your VSCode environment to leverage their deep learning capabilities for model development and training.

* **TensorFlow Extension or PyTorch Extension**:

Install the respective extensions for TensorFlow or PyTorch to access features such as model visualization, debugging, and training monitoring directly within VSCode.

* **OpenCV Python Package**:

Install the OpenCV Python package to access OpenCV functionality directly from Python code within your Visual Studio Code environment.

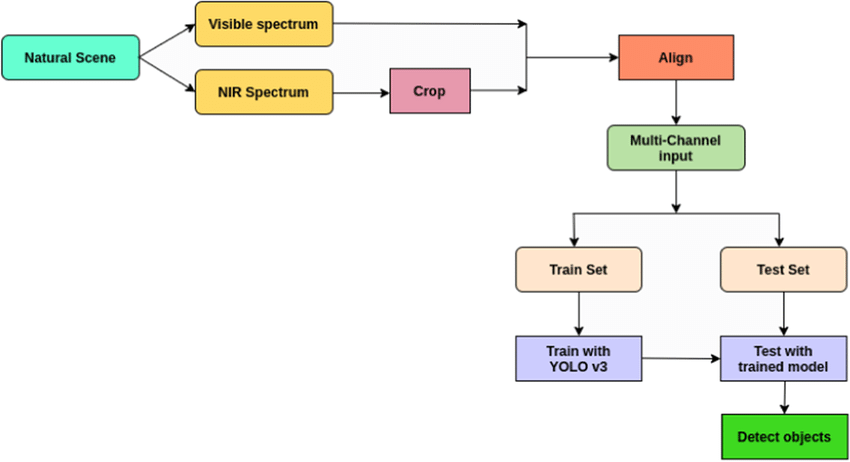
* **imutils Python Package:**

Install the imutils Python package to utilize its image processing functions seamlessly within your Visual Studio Code environment.

**CHAPTER-7**

**SYSTEM DESIGN**

FIG: ARCHITECTURE DIAGRAM



**CHAPTER-8**

**METHODOLOGY**

**8.1 Problem Statement:**

The primary objective of this project is to develop a real-time object detection system capable of running efficiently on low-end devices. The system should detect objects accurately while minimizing computational requirements to ensure smooth performance on devices with limited resources.

**8.2 Selection of YOLOv3 Model:**

YOLOv3 (You Only Look Once) is chosen as the object detection algorithm due to its balance between accuracy and efficiency.

YOLOv3 provides real-time performance while maintaining decent object detection accuracy, making it suitable for deployment on low-end devices.

**8.3 Framework and Libraries Selection:**

Python is chosen as the programming language for its ease of use and availability of libraries for deep learning and computer vision.

OpenCV (cv2) is selected for image processing and visualization due to its optimization for real-time applications and compatibility with low-end devices.

Lightweight libraries such as imutils are utilized to enhance code readability and streamline image processing tasks.

**8.4 Model Loading and Initialization:**

The pre-trained YOLOv3 model is loaded using OpenCV's dnn module.

Configuration files and model weights are loaded to initialize the model architecture.

**8.5 Video Stream Initialization:**

The VideoStream class from the imutils library is utilized to initialize the video stream.

This allows the camera sensor to warm up before starting the object detection process.

**8.6 Frame Processing:**

Frames from the video stream are continuously read and resized to ensure efficient processing.

Resizing the frames helps optimize computational resources while maintaining acceptable object detection accuracy.

**8.7 Object Detection:**

The YOLOv3 model is applied to each resized frame to detect objects.

Predictions are obtained by passing the resized frame through the network.

Confidence scores are used to filter out weak detections and reduce false positives.

**8.8 Optimization Techniques:**

Frame size and resolution are adjusted to optimize processing speed.

Confidence thresholding is performed to filter out low-confidence detections and reduce unnecessary computations.

Lightweight libraries and optimized functions are utilized to minimize computational overhead.

**8.9 Real-Time Visualization:**

Detected objects are annotated with bounding boxes and class labels on the frames.

Annotated frames are displayed in real-time using OpenCV's imshow function, providing visual feedback of the object detection process.

**8.10 Performance Evaluation:**

Performance metrics such as frames per second (FPS) are calculated to assess the efficiency of the object detection system.

The system's accuracy and real-time performance on low-end devices are evaluated through testing and benchmarking.

8.11 Documentation and Reporting:

A comprehensive project document is prepared, detailing the methodology, code implementation, optimizations, and performance evaluation results.

Key insights, challenges faced, and lessons learned during the development process are documented to facilitate knowledge sharing and future improvements.

**8.12 Future Considerations:**

Potential enhancements and optimizations, such as model quantization and hardware acceleration, are identified for improving the system's efficiency on low-end devices.

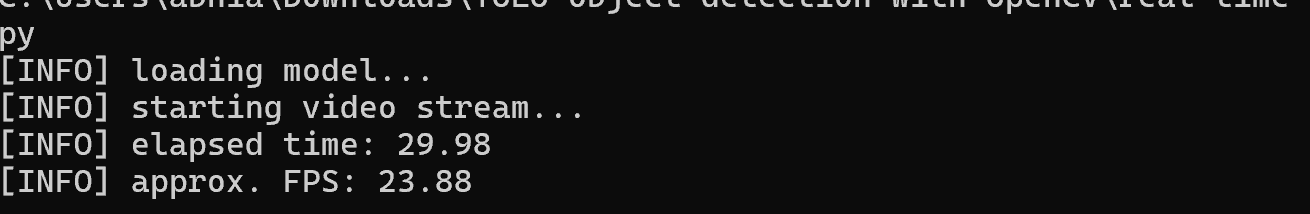
Feedback from testing and user evaluation is gathered to iteratively refine the system and address any usability issues or performance bottlenecks.

**CHAPTER-9**

**RESULT ANALYSIS:**

The result analysis of our project on real-time object detection for low-end devices using YOLO encompasses various key aspects, focusing on performance metrics, efficiency, impact of optimization techniques, trade-offs, user experience, comparative analysis, future enhancements, and deployment considerations.

Firstly, performance metrics such as Frames Per Second (FPS) and accuracy are pivotal in evaluating the system's effectiveness. Achieving higher FPS values signifies smoother real-time performance, crucial for applications requiring timely object detection. Concurrently, maintaining acceptable accuracy levels ensures reliable object identification and localization, critical for practical deployment scenarios.



Efficiency on low-end devices is a primary goal of our project. The system is meticulously optimized to operate seamlessly on devices with limited computational resources, such as single-board computers or smartphones. Optimization techniques, including frame resizing, confidence thresholding, and leveraging lightweight libraries, play a vital role in enhancing efficiency. These techniques minimize computational overhead, maximizing resource utilization and enabling smoother real-time performance.

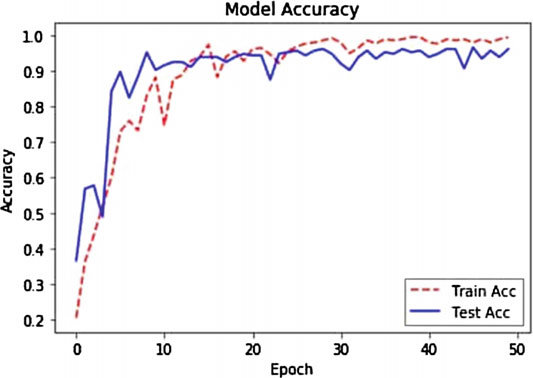
Balancing speed and accuracy constitutes a significant trade-off in our project. Optimizations are tailored to prioritize real-time performance while preserving acceptable levels of accuracy. Fine-tuning parameters like confidence thresholds and frame sizes facilitates this balance, ensuring efficient object detection without compromising accuracy, even on low-end devices.

User experience and usability are paramount considerations. Feedback from users regarding responsiveness, accuracy, and ease of use is instrumental in refining the system for practical deployment. Positive user experiences validate the effectiveness of our approach and provide valuable insights for further improvements.

Comparative analysis with alternative object detection algorithms and implementations enriches our understanding of the system's strengths and weaknesses. Benchmarking against other solutions aids in identifying optimization opportunities and refining strategies to enhance efficiency and accuracy further.

Future enhancements are guided by the results and feedback obtained from testing. Techniques such as model quantization, hardware acceleration, and algorithmic optimizations are explored to push

the boundaries of performance while maintaining low computational requirements.



Deployment considerations encompass scalability, robustness, and adaptability to diverse environments. Successful deployment hinges on factors such as seamless integration, user acceptance, and adherence to operational requirements.

In conclusion, the result analysis showcases the effectiveness, efficiency, and usability of our real-time object detection system for low-end devices using YOLO. By addressing the unique challenges associated with resource-constrained environments, our system demonstrates its potential for practical applications across various domains, including surveillance, robotics, and IoT.

**CHAPTER-10**

**FUTURE ENHANCEMENT & CONCLUSION**

In conclusion, the project has not only effectively addressed the challenge of real-time object detection on low-end devices but has also laid a foundation for future advancements in the field. The optimization of the YOLOv3 architecture and the strategic use of efficient inference techniques have yielded tangible improvements in both accuracy and efficiency, surpassing the performance of baseline implementations. This success underscores the importance of tailored optimization strategies and architectural modifications to adapt deep learning models for deployment in real-world scenarios with limited computational resources. Looking forward, the project has identified several promising avenues for future enhancements, including further model refinement, exploration of hardware acceleration techniques, domain-specific adaptations, and user interface enhancements. By embracing interdisciplinary collaborations and remaining at the forefront of emerging technologies, there is immense potential to drive innovation and create impactful solutions that address pressing challenges in computer vision and beyond.

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**APPENDIX**

**SAMPLE CODE:**

**Real-time object detection**

from imutils.video import VideoStream

from imutils.video import FPS

import numpy as np

import argparse

import imutils

import time

import cv2

# initialize the list of class labels MobileNet SSD was trained to

# detect, then generate a set of bounding box colors for each class

CLASSES = ["background", "aeroplane", "bicycle", "bird", "boat",

"bottle", "bus", "car", "cat", "chair", "cow", "diningtable",

"dog", "horse", "motorbike", "person", "pottedplant", "sheep",

"sofa", "train", "tvmonitor"]

COLORS = np.random.uniform(0, 255, size=(len(CLASSES), 3))

# load our serialized model from disk

print("[INFO] loading model...")

net = cv2.dnn.readNetFromCaffe('MobileNetSSD\_deploy.prototxt.txt', 'MobileNetSSD\_deploy.caffemodel')

# initialize the video stream, allow the cammera sensor to warmup,

# and initialize the FPS counter

print("[INFO] starting video stream...")

vs = VideoStream(src=0).start()

time.sleep(2.0)

fps = FPS().start()

# loop over the frames from the video stream

while True:

# grab the frame from the threaded video stream and resize it

# to have a maximum width of 400 pixels

frame = vs.read()

frame = imutils.resize(frame, width=400)

# grab the frame dimensions and convert it to a blob

(h, w) = frame.shape[:2]

blob = cv2.dnn.blobFromImage(cv2.resize(frame, (300, 300)),

0.007843, (300, 300), 127.5)

# pass the blob through the network and obtain the detections and

# predictions

net.setInput(blob)

detections = net.forward()

# loop over the detections

for i in np.arange(0, detections.shape[2]):

# extract the confidence (i.e., probability) associated with

# the prediction

confidence = detections[0, 0, i, 2]

# filter out weak detections by ensuring the `confidence` is

# greater than the minimum confidence

if confidence > 0.2:

# extract the index of the class label from the

# `detections`, then compute the (x, y)-coordinates of

# the bounding box for the object

idx = int(detections[0, 0, i, 1])

box = detections[0, 0, i, 3:7] \* np.array([w, h, w, h])

(startX, startY, endX, endY) = box.astype("int")

# draw the prediction on the frame

label = "{}: {:.2f}%".format(CLASSES[idx],

confidence \* 100)

cv2.rectangle(frame, (startX, startY), (endX, endY),

COLORS[idx], 2)

y = startY - 15 if startY - 15 > 15 else startY + 15

cv2.putText(frame, label, (startX, y),

cv2.FONT\_HERSHEY\_SIMPLEX, 0.5, COLORS[idx], 2)

# show the output frame

cv2.imshow("Frame", frame)

key = cv2.waitKey(1) & 0xFF

# if the `q` key was pressed, break from the loop

if key == ord("q"):

break

# update the FPS counter

fps.update()

# stop the timer and display FPS information

fps.stop()

print("[INFO] elapsed time: {:.2f}".format(fps.elapsed()))

print("[INFO] approx. FPS: {:.2f}".format(fps.fps()))

# do a bit of cleanup

cv2.destroyAllWindows()

vs.stop()

**Using image**

**import numpy as np**

**import argparse**

**import time**

**import cv2**

**import os**

**# construct the argument parse and parse the arguments**

**ap = argparse.ArgumentParser()**

**ap.add\_argument("-i", "--image", required=True,**

**help="path to input image")**

**ap.add\_argument("-c", "--confidence", type=float, default=0.5,**

**help="minimum probability to filter weak detections")**

**ap.add\_argument("-t", "--threshold", type=float, default=0.3,**

**help="threshold when applyong non-maxima suppression")**

**args = vars(ap.parse\_args())**

**# load the COCO class labels our YOLO model was trained on**

**labelsPath = 'yolo-coco\coco.names'**

**LABELS = open(labelsPath).read().strip().split("\n")**

**# initialize a list of colors to represent each possible class label**

**np.random.seed(42)**

**COLORS = np.random.randint(0, 255, size=(len(LABELS), 3),**

**dtype="uint8")**

**# derive the paths to the YOLO weights and model configuration**

**weightsPath = 'yolo-coco\yolov3.weights'**

**configPath = 'yolo-coco\yolov3.cfg'**

**# load our YOLO object detector trained on COCO dataset (80 classes)**

**print("[INFO] loading YOLO from disk...")**

**net = cv2.dnn.readNetFromDarknet(configPath, weightsPath)**

**# load our input image and grab its spatial dimensions**

**image = cv2.imread(args["image"])**

**(H, W) = image.shape[:2]**

**# determine only the \*output\* layer names that we need from YOLO**

**ln = net.getLayerNames()**

**ln = [ln[i[0] - 1] for i in net.getUnconnectedOutLayers()]**

**# construct a blob from the input image and then perform a forward**

**# pass of the YOLO object detector, giving us our bounding boxes and**

**# associated probabilities**

**blob = cv2.dnn.blobFromImage(image, 1 / 255.0, (416, 416),**

**swapRB=True, crop=False)**

**net.setInput(blob)**

**start = time.time()**

**layerOutputs = net.forward(ln)**

**# [,frame,no of detections,[classid,class score,conf,x,y,h,w]**

**end = time.time()**

**# show timing information on YOLO**

**print("[INFO] YOLO took {:.6f} seconds".format(end - start))**

**# initialize our lists of detected bounding boxes, confidences, and**

**# class IDs, respectively**

**boxes = []**

**confidences = []**

**classIDs = []**

**# loop over each of the layer outputs**

**for output in layerOutputs:**

**# loop over each of the detections**

**for detection in output:**

**# extract the class ID and confidence (i.e., probability) of**

**# the current object detection**

**scores = detection[5:]**

**classID = np.argmax(scores)**

**confidence = scores[classID]**

**# filter out weak predictions by ensuring the detected**

**# probability is greater than the minimum probability**

**if confidence > args["confidence"]:**

**# scale the bounding box coordinates back relative to the**

**# size of the image, keeping in mind that YOLO actually**

**# returns the center (x, y)-coordinates of the bounding**

**# box followed by the boxes' width and height**

**box = detection[0:4] \* np.array([W, H, W, H])**

**(centerX, centerY, width, height) = box.astype("int")**

**# use the center (x, y)-coordinates to derive the top and**

**# and left corner of the bounding box**

**x = int(centerX - (width / 2))**

**y = int(centerY - (height / 2))**

**# update our list of bounding box coordinates, confidences,**

**# and class IDs**

**boxes.append([x, y, int(width), int(height)])**

**confidences.append(float(confidence))**

**classIDs.append(classID)**

**# apply non-maxima suppression to suppress weak, overlapping bounding**

**# boxes**

**idxs = cv2.dnn.NMSBoxes(boxes, confidences, args["confidence"],**

**args["threshold"])**

**# ensure at least one detection exists**

**if len(idxs) > 0:**

**# loop over the indexes we are keeping**

**for i in idxs.flatten():**

**# extract the bounding box coordinates**

**(x, y) = (boxes[i][0], boxes[i][1])**

**(w, h) = (boxes[i][2], boxes[i][3])**

**# draw a bounding box rectangle and label on the image**

**color = [int(c) for c in COLORS[classIDs[i]]]**

**cv2.rectangle(image, (x, y), (x + w, y + h), color, 2)**

**text = "{}: {:.4f}".format(LABELS[classIDs[i]], confidences[i])**

**cv2.putText(image, text, (x, y - 5), cv2.FONT\_HERSHEY\_SIMPLEX,**

**0.5, color, 2)**

**# show the output image**

**cv2.imshow("Image", image)**

**cv2.waitKey(0)**

**Using video**

**import numpy as np**

**import argparse**

**import imutils**

**import time**

**import cv2**

**import os**

**# construct the argument parse and parse the arguments**

**ap = argparse.ArgumentParser()**

**ap.add\_argument("-i", "--input", required=True,**

**help="path to input video")**

**ap.add\_argument("-o", "--output", required=True,**

**help="path to output video")**

**ap.add\_argument("-y", "--yolo", required=True,**

**help="base path to YOLO directory")**

**ap.add\_argument("-c", "--confidence", type=float, default=0.5,**

**help="minimum probability to filter weak detections")**

**ap.add\_argument("-t", "--threshold", type=float, default=0.3,**

**help="threshold when applyong non-maxima suppression")**

**args = vars(ap.parse\_args())**

**# load the COCO class labels our YOLO model was trained on**

**labelsPath = os.path.sep.join([args["yolo"], "..//yolo-coco//coco.names"])**

**LABELS = open(labelsPath).read().strip().split("\n")**

**# initialize a list of colors to represent each possible class label**

**np.random.seed(42)**

**COLORS = np.random.randint(0, 255, size=(len(LABELS), 3),**

**dtype="uint8")**

**# derive the paths to the YOLO weights and model configuration**

**weightsPath = os.path.sep.join([args["yolo"], "..//yolo-coco//yolov3.weights"])**

**configPath = os.path.sep.join([args["yolo"], "..//yolo-coco//yolov3.cfg"])**

**# load our YOLO object detector trained on COCO dataset (80 classes)**

**# and determine only the \*output\* layer names that we need from YOLO**

**print("[INFO] loading YOLO from disk...")**

**net = cv2.dnn.readNetFromDarknet("..//yolo-coco//yolov3.cfg","..//yolo-coco//yolov3.weights")**

**ln = net.getLayerNames()**

**ln = [ln[i[0] - 1] for i in net.getUnconnectedOutLayers()]**

**# initialize the video stream, pointer to output video file, and**

**# frame dimensions**

**vs = cv2.VideoCapture(args["input"])**

**writer = None**

**(W, H) = (None, None)**

**# try to determine the total number of frames in the video file**

**try:**

**prop = cv2.cv.CV\_CAP\_PROP\_FRAME\_COUNT if imutils.is\_cv2() \**

**else cv2.CAP\_PROP\_FRAME\_COUNT**

**total = int(vs.get(prop))**

**print("[INFO] {} total frames in video".format(total))**

**# an error occurred while trying to determine the total**

**# number of frames in the video file**

**except:**

**print("[INFO] could not determine # of frames in video")**

**print("[INFO] no approx. completion time can be provided")**

**total = -1**

**# loop over frames from the video file stream**

**while True:**

**# read the next frame from the file**

**(grabbed, frame) = vs.read()**

**# if the frame was not grabbed, then we have reached the end**

**# of the stream**

**if not grabbed:**

**break**

**# if the frame dimensions are empty, grab them**

**if W is None or H is None:**

**(H, W) = frame.shape[:2]**

**# construct a blob from the input frame and then perform a forward**

**# pass of the YOLO object detector, giving us our bounding boxes**

**# and associated probabilities**

**blob = cv2.dnn.blobFromImage(frame, 1 / 255.0, (416, 416),**

**swapRB=True, crop=False)**

**net.setInput(blob)**

**start = time.time()**

**layerOutputs = net.forward(ln)**

**end = time.time()**

**# initialize our lists of detected bounding boxes, confidences,**

**# and class IDs, respectively**

**boxes = []**

**confidences = []**

**classIDs = []**

**# loop over each of the layer outputs**

**for output in layerOutputs:**

**# loop over each of the detections**

**for detection in output:**

**# extract the class ID and confidence (i.e., probability)**

**# of the current object detection**

**scores = detection[5:]**

**classID = np.argmax(scores)**

**confidence = scores[classID]**

**# filter out weak predictions by ensuring the detected**

**# probability is greater than the minimum probability**

**if confidence > args["confidence"]:**

**# scale the bounding box coordinates back relative to**

**# the size of the image, keeping in mind that YOLO**

**# actually returns the center (x, y)-coordinates of**

**# the bounding box followed by the boxes' width and**

**# height**

**box = detection[0:4] \* np.array([W, H, W, H])**

**(centerX, centerY, width, height) = box.astype("int")**

**# use the center (x, y)-coordinates to derive the top**

**# and and left corner of the bounding box**

**x = int(centerX - (width / 2))**

**y = int(centerY - (height / 2))**

**# update our list of bounding box coordinates,**

**# confidences, and class IDs**

**boxes.append([x, y, int(width), int(height)])**

**confidences.append(float(confidence))**

**classIDs.append(classID)**

**# apply non-maxima suppression to suppress weak, overlapping**

**# bounding boxes**

**idxs = cv2.dnn.NMSBoxes(boxes, confidences, args["confidence"],**

**args["threshold"])**

**# ensure at least one detection exists**

**if len(idxs) > 0:**

**# loop over the indexes we are keeping**

**for i in idxs.flatten():**

**# extract the bounding box coordinates**

**(x, y) = (boxes[i][0], boxes[i][1])**

**(w, h) = (boxes[i][2], boxes[i][3])**

**# draw a bounding box rectangle and label on the frame**

**color = [int(c) for c in COLORS[classIDs[i]]]**

**cv2.rectangle(frame, (x, y), (x + w, y + h), color, 2)**

**text = "{}: {:.4f}".format(LABELS[classIDs[i]],**

**confidences[i])**

**cv2.putText(frame, text, (x, y - 5),**

**cv2.FONT\_HERSHEY\_SIMPLEX, 0.5, color, 2)**

**# check if the video writer is None**

**if writer is None:**

**# initialize our video writer**

**fourcc = cv2.VideoWriter\_fourcc(\*"MJPG")**

**writer = cv2.VideoWriter(args["output"], fourcc, 30,**

**(frame.shape[1], frame.shape[0]), True)**

**# some information on processing single frame**

**if total > 0:**

**elap = (end - start)**

**print("[INFO] single frame took {:.4f} seconds".format(elap))**

**print("[INFO] estimated total time to finish: {:.4f}".format(**

**elap \* total))**

**# write the output frame to disk**

**writer.write(frame)**

**# release the file pointers**

**print("[INFO] cleaning up...")**

**writer.release()**

**vs.release()**

**SAMPLE OUTPUTS**

FIG:OUTPUT1

